An Efficient Vision-based Approach for Optimizing Energy Consumption in Internet of Things and Smart Homes

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***Abstract*—One of the primary forces for digital transformation is how quickly the world is changing. Additionally, and at a dizzying pace, the world economy is being transformed by digital technology. The billions of daily online connections between individuals, organizations, devices, data, and processes that generate economic activity are known as the "digital economy." The Internet, mobile technology, and the Internet of Things (IoT) all contribute to hyper-interconnection, or the growing connectivity of people, organizations, and machines, which is the foundation of the digital economy. Simultaneously with these developments, the demand for energy is more than the supply, which leads to energy shortage. In order to keep pace with energy demand, new strategies are being developed. As a result of the emergence and expansion of smart homes, there is a growing need for digitization in applications such as energy efficient automation and safety. With the increase in the amount of electricity consumed and the introduction of new energy sources, the reduction of electricity costs for households becomes increasingly important. Basically, this article uses machine vision technology. In this paper, a YOlO method is used for facial recognition. And compared to all kinds of YOlO methods, the YOlOv5n method was the fastest and most efficient method. So, by using the YOlOv5s method on the Jetson Nano platform, it creates the possibility of authenticating the residents of the houses to identify them to turn on or off the sources of energy consumption in the houses. Therefore, the presented system is designed with the aim of optimizing energy consumption in houses and with the aim of ensuring the safety of the residents of the houses.**

Keywords*—IoT; Internet of things; digital economics; smart cities; digitization; machine vision; YOLO; YOLOv5n

I. Introduction

Don Tapscott, an internationally recognized expert on the economic and social effects of technology, popularized the phrase "Digital Economy" in his 1994 book "The Digital Economy: Promise and Peril in the Age of Networked Intelligence." Information in all of its forms is converted to digital form in the new [digital] economy, where it is stored as bits in computers and sent over networks at the speed of light. Although the digital economy did not have a single beginning, significant turning points in its history include the invention of the internet and the introduction of personal computers in the early 1980s, the creation of the world wide web in 1989 and the public launch of that platform in the early 1990s, as well as the introduction of the first smartphones in the late 1990.

The Internet of Things (IoT) is a prevalent concept and an essential part of daily living. which are employed in a wide range of fields, such as transportation, healthcare, and industry, as well as smart homes and smart cities from a security standpoint, it appears that both intelligent devices and users must start a safe communication channel in order to recognize digital form. IoT offers a wide range of options for assisting people in carrying out their regular tasks.

The Internet of Things (IoT) today provides a powerful tool that not only connects wireless communication devices but also remote sensors for heating/cooling or any other necessary utility inside the building to more likely regulate energy usage and improve the living experience in modern homes [1] . A smart home is a house that has been incorporated into the Internet of Things (IoT) and offers its residents comfort, security, convenience, improved quality of life [2]. The IoT is the underpinning platform of a smart home network that connects various smart devices, including wearables, smart meters, and smartphones. Smart home technologies have the potential to improve and facilitate people's lives and independence.

Modern civilization is undergoing a trend known as "smart home technology," which creates intelligent living spaces for daily comfort and ease [3]. Smart homes are automated structures with control, monitoring, and detecting hardware and systems, including heating and cooling, lighting, ventilation, and security. Gateways are the name given to these contemporary systems, which include sensors and switches and communicate via a central axis. These gateways are control systems with user interfaces for smartphones, tablets, and computers. The Internet of Things controls the communication network (IoT).

The quality of human life, well-being, productivity, energy efficiency, and safety may all be impacted by the usage of smart technology in a house, building, or environment, including sensors, actuators, and artificial intelligence (AI) [4]. According to the chart below, the share of energy efficiency among smart home technology trends was 31% in 2018 and increased to 42% in 2020 and is in third place.

In the following, the second part of study refers to studies from 2020 to 2021 in the field of using the Internet of Things to optimize energy consumption in smart homes. The third part defines the methodology, the fourth part specifies results and model evaluation. The fifth part of the findings and finally the sixth part refers to the conclusion and future studies.

The main research contributions of this study are as follows,

1) The research paper introduces a facial recognition method based on YOLOv5n, showcasing enhanced efficiency and speed compared to other YOLO methods.

2) The integration of YOLOv5s onto the Jetson Nano platform enables the deployment of facial recognition systems for energy consumption optimization in residential houses with limited resources.

3) The presented system combines facial recognition technology with energy management, aiming to optimize energy consumption in houses while ensuring the safety of residents.

II. Related Works

By favoring various types of equipment, people nowadays are ignoring the cost and usage of electricity. Numerous innovative methods of controlling, tracking, and monitoring a home's energy savings have emerged as a result of rising energy prices and demand [5].

A new generation of homes called "smart homes" has been made possible by improvements in energy conversion, communication, and information technologies. These homes allow individuals to enhance the comfort, convenience, safety, and entertainment of their homes while also reducing energy waste. In many nations, Home Energy Management Systems (HEMS) are crucial for accomplishing the objectives of smart energy houses. The market for smart homes is expanding quickly as well. It is particularly getting better in areas like energy efficiency systems, lighting, entertainment, and fire detection, among others.

In Table I studies regarding the optimization of energy consumption through the Internet of Things in smart homes in 2020 to 2021 are presented.

TABLE I. Related Works

Models and Reference	Method / Applications	Advantages / Disadvantages
An Elman recurrent neural network model and exponential model [6].	the Real-Time Power and Intelligent Systems (RTPIS) laboratory	The Elman RNN model outperforms the exponential model and it is a more efficient approach for real-time and near future electric energy consumption estimation and prediction in an IoT driven building environment. The model will be employed to minimize inefficient energy management
HEMS-IoT (relying on J48 & Weka API, RuleML and Apache Mahout, [1]	Smart homes in Mexico	HEMS-IoT estimates more energy consumption reduction The application only works on Android, system compatibility with only some sensors, only using big data and J48, not recommending energy saving, HEMS-IoT implementation relying on GPS of mobile devices.
Holt-Winters-RNN, M4 Forecasting Competition, symmetric mean absolute percentage error (sMAPE), a multilayer perceptron ANN [7].	IntelliHome smart-home system/ a residential housing complex containing 20 units/Using the R programming language	The lowest sMAPE with Holt-Winters-RNN Using out-of-home data with users' smartphones and developing a native mobile application for Android OS using a cross-platform application development framework such as Angular, Ionic or Cordova
deep extreme learning machine (DELM), Bat algorithm and fuzzy logic [8].	https://github.com/LuisM78/Appliances-energy-predictiondata	Inability to change static user parameters, predicted user parameters have improved overall system performance in terms of ease of use of smart systems, energy consumption and comfort index management. After optimization, the power consumption also decreased and remained at around 15-18 Wh.
an efficient approach for DLC with day-ahead optimization using edge and fog computing, Cloud, fog and edge computing, proving that the integration of IoT and communication protocols such as MQTT[9].	114 single-family houses that form a small community with modern and flexible appliances	Total daily used flexibility and the number of interruptions decreased, Maximum number of interruptions per appliance decreased, while Peak to Average Ratio (PAR) improved when implementing the proposed DLC architecture. Possible future study of mechanisms for sharing surpluses and exchanges between communities The main shortcomings are related to the regulatory framework to adopt the DLC for energy communities
Internet-of-Things (IoT), Wireless Sensor Network (WSN), and a structure of a Sensor Node (SN), DVFS, [10]	Multiprocessor System-on-Chip (MPSoC) platform	Energy-aware approaches that are able to Computational system considerations are not the total power model The lack of scheduling work on processors considering processor temperature and work constraints. Inefficiency to address the communication gap problem in NoC links for heterogeneous MPSoC systems, inadequacy to create an optimal balance between DPM and DVFS for scalable work,
smart grid architecture model (SGAM)[11].	various control functions, incorporated in the local power controller (LPC) or distributed systems, SECS architecture called SmartCom	Reduction of energy losses by (SECS) due to the possibility of ventilation and control of residential energy consumption, data logging by the (IoT), smart sockets (SO) and devices that promote indoor user identification (UII) environments. a way to help balance energy with minimal impact on the daily usability of electrical equipment. Widespread implementation of sensors throughout the residence Misinterpretation of data generated by residents
identification and tracking of multiple users by internal Wi-Fi handover by making use of smartphones, and through the use of SO technology using	Home Energy Management Systems (HEMS) architecture	Technological requirements: the high degree of flexibility and reuse, service transparency, availability of information and modularity. An ability to predict the final amount of energy consumption by using an intelligent module, A Design and control consumption system for both the customer and the

NFC identification to extract accurate data from [12].		power companies, A tracking system for residential homes with multiple residents with the purpose of improving the management of electricity consumption.
a fully automated IoT-based hierarchical framework for smart homes that takes advantage of edge-computing devices for data processing and storage [13].	Resource-constrained Raspberry Pi (RPI)	The proposed system is 5% faster in motion detection and 6% more efficient in terms of energy consumption than existing solutions. This is done through human detection, fire and interior construction detection, suspicious activity detection, etc. Future work: Using RPI for inexpensive multimedia data processing
Tolojescu- Crisan [14].	qToggle, ESP8266 chips and Raspberry Pi boards	qToggle is simple and flexible, more integrated, more secure, instant updates. Users without technical background Future plan: A feature that will be added to qToggle soon is humidity monitoring, integrate video surveillance into qToggle.

III. Methodology

A. Proposed System Architecture

Due to its understanding of its own things, a smart house provides its people with individualized services. Homes should not only consume less energy but also be more livable and productive because the home environment influences people's quality of life and capacity to work. When using 2D cameras as sensors, deployment should be adjusted so that the financial gains from energy savings outweigh the associated expenses. Controlling the entire home is not practicable nor possible, it should be stressed. In addition to the activity patterns identified by data monitoring, actual 2D camera sensor data on such inputs should be used to optimize final energy management and consumption. Consequently, the gadget can adjust to new circumstances that were not present in the early models, as well as changes in the setting of the house. The three layers that make up this platform's design are sufficiently all-encompassing to address the requirements of various smart settings, including those considered in the context of smart homes. The IoT-based smart home's three-layer structure is as follows:

Layer 1: Measuring or interpreting sensor data in accordance with user preferences and saving this information in a separate cloud server through a network gateway.

Layer 2: Processing and arranging data gathered from user personal information at.

Layer 3: Data reproduction or application layer, which repeats processed data as information about specific interactions between users and equipment and applies the gathered data to enhance the functionality and performance of the device and provide users better services.

A framework with sensors that assess power use has been created in order to enhance home maintenance and make homes "smart" and efficient. In order to assess if someone is at home, the user may also use the motion sensor's processed data from the cloud service, which offer the meaning of "safe." Additionally, a voltage stabilizer will automatically operate on the installed cloud server to prevent any problems. Users may easily connect to the network using their phone service thanks to the building's Wi-Fi connection. Smart technology enables users to make their homes safer. Among the smart home devices, cameras set throughout the home enable environment monitoring from a phone or other device as needed. Residents will interact with the security system through their mobile or smart phone interfaces. The safety system reacts when it notices motion or unusual movement. As a result, it is clear that this intelligent defense is far more dependable and trustworthy than the emergency siren. To guarantee the effective and efficient operation of all gadgets, residents will also receive the home equipment power consumption control program. Therefore, here are some of the main advantages of our smart home architecture: optimizing and reducing energy consumption, increasing the performance of the home, identify the source of electrical energy leakage, predictive maintenance improves capital use, increasing the security of the home according to the alarm system based on the presence or absence of inhabitants.

B. Proposed System

The regulation of energy consumption results in lower energy use throughout the house [16]. The suggested system's objective is to control or lower energy usage by machine vision. A subset of artificial intelligence is machine vision [17]. This technology uses two-dimensional cameras that are already placed in homes as vision sensors from the automobile to decrease the amount of power used. The proposed system detects whether a person is a resident or a non-resident when they enter the house. Of course, this also applies when they depart, and if a resident leaves the house, power is turned on. Electrical equipment is switched off, and if a visitor departs, the system detects him as a stranger and does not turn off the electrical equipment. This paper presents a smart home energy management system that includes 2D cameras, electric vehicles and energy storage units. The process of the system is provided in Fig. 1.

C. Resident Authentication

People may now be identified using a number of different authentication techniques. These techniques include visual biometric devices such as retina scans, iris recognition, fingerprint scanning, hand geometry recognition, ear authentication, signature recognition, and facial recognition as well as chemical biometric devices such as DNA (deoxyribonucleic acid) matching and vein or vascular scanners such as Finger vein ID. Behavioral identifiers such as gait and typing recognition are also included. The facial recognition approach is employed in this investigation.

1) Face recognition process: The system will upload photographs into the recognized member's database for the facial recognition procedure. Any new record may be added as needed to the database [18]. Add a fresh photo and the face registration name to the database. Face recognition uses the picture that is retrieved from the database and compared to the image that was collected to identify the subject in the front camera module. The door will open if a match is found in the faces. If not, a red bulb will come on. The bell will ring if it is the home's owner. If not, a message that someone is waiting outside your house will be issued. When the image of an unfamiliar individual is found, this system provides alerts.

2) Face recognition platform: The facial recognition algorithm is included in Jetson Nano. In this system, data is sent via the cloud to a remote server from a smartphone. An IoT-based system can be implemented to automate the authentication process for security purposes. The electricity and power consumption in this system is low because it needs very little electricity. It needs at least five volts to work. The Nano Jetson module includes the TensorRT-powered AI development kit in JetPack. It allows the processing of complex deep learning algorithms. The specifications of the Jetson Nano used are as follows:

GPU: 128-core NVIDIA Maxwell

CPU: Quad-core ARM A57 @ 1.43 GHz

Memory: 2 GB 64-bit LPDDR4 25.6 GB/s

Storage microSD (Card not included)

Camera 1x MIPI CSI-2 connector

3) YOLO based face recognition: The YOLOv5 based algorithm used for facial recognition. A single neural network was utilized by YOLO to identify and estimate positions. It predicts the positions of items based on the characteristics of the entire picture [4]. The four network model variations of YOLOv5—YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x—are based on the differences in network depth and breadth. According to the literature, the YOLOv5s network's detection and placement speed is quicker than YOLOv4's, and its accuracy is comparable. The backbone, neck, and head are the three primary parts of the YOLOv5 network. Backbone gathers and creates image characteristics on various pictures when the image is input. Next, the Head predicts the image characteristics to provide bounding boxes and predicted categories after the Neck stitches the image features and delivers them to the prediction layer. The GIOU is the network loss function used by the YOLOv5 network, as illustrated in Equation (1).

$$\mathrm{GIOU} = \mathrm{IOU} - \frac{|C-(A\cup B)|}{|C|} \quad (1)$$

Where $A,B \subseteq S \subseteq R^n$ represent two arbitrary boxes. C represents the smallest convex box, $C \subseteq S \subseteq R^n$, enclosing both A and B and $IOU=|A\cap B| / |A\cup B|$.

Combining the GIOU loss function with the non-maximum suppression method filters the best target frame when the input network predicts picture features [15].

D. Dataset

In this research, a dataset including 500 images was used. The images are about 50 people and collect 10 images from each. Among them, 80% of the images were used for training and 20% for evaluation. These images are labeled according to the training and evaluation of the YOLOv5 model. The YOLO pattern was used to label the images. The images are labeled in ten classes for each person.

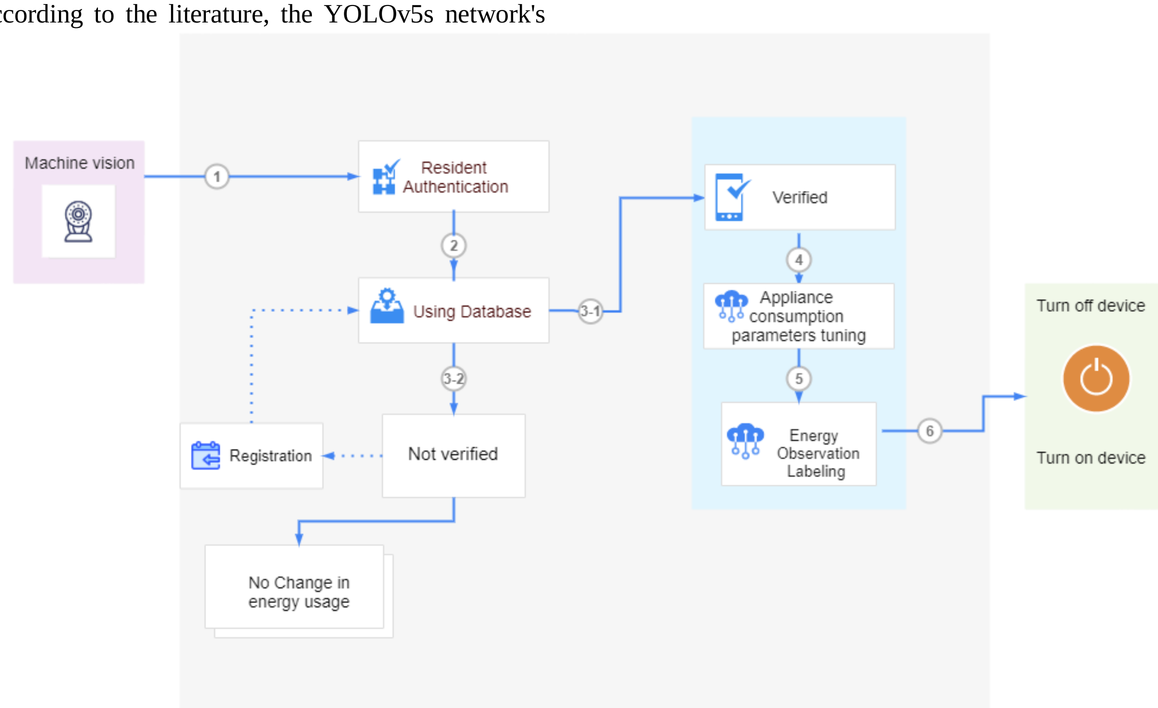

Fig. 1. Proposed system.

E. Model Generation

In this study, transfer learning is used to retrain algorithms YOLOv5 series which is based on the dataset of common objects in the field (COCO). This dataset was trained with 330 thousand images and 80 classes. This model is used as pretrained model for transfer learning. In modeling, it is used a batch size of 16 and 100 epochs. The modeling processes are performed for different versions of YOLOv5. These versions are v5n, v5s, v5m, v5l, v5x. The model with deep layers performs better in training and converges faster, as seen by the results while training with the same number of repetitions. The v5n model in more epochs is reached in balance and the error has been minimized, but in the v5x model, there is an error in fewer epochs' energy storage units.

IV. RESULTS AND MODEL EVALUATION

This section presents experimental results and performance analysis for face recognition using different YOLOv5 models.

A. Performance Metric

Performance analysis is checked in this section. The generated model based on YOLOv5 is evaluated. In this study, Precision, Recall, F1 and mAP metrics are used for evaluation of the model.

The first three metrics are computed by TP (true positive), TN (true negative), FP (false positive) and FN (false negative). The explanations are shown in Table II.

TABLE II. THE METRICS DEFINITION FOR PERFORMANCE ANALYSIS

Metric	Explanations
TP	Refers to how many faces are successfully identified
TN	Refers to how many backgrounds are identified as backgrounds
FP	Refers to the number of backgrounds that are wrongly identified as backgrounds
FN	Refers to the number of faces that were misclassified as a backdrop

Precision (P): The precision determines the accuracy and reliability of the positive answers of the models being correct. Equation 2 presents how the P metric is calculated.

$$P = \frac{TP}{TP+FP} \quad (2)$$

Recall (R): Recall metric determines the ability and sensitivity of the models in performing the correct classification. According to equation 3, this is done by calculating the ratio of correct positive answers to the sum of correct positive answers and false negative answers. This standard is also known as the correct positive response rate and model accuracy rate.

$$R = \frac{TP}{TP+FN} \quad (3)$$

F1-score: F-score is determined according to equation 4 by calculating the equivalent weighted average of two metrics, Precision(P) and Recall(R). The detection rate of positive samples, which is the difference between the evaluation metrics, is considered by both precision and recall in the R-P curve. A more visual way to evaluate the models is the average accuracy (AP), which represents the area under the R-P curve (AUC), higher AP means better machine learning model. mAP is an average of AP values. Therefore, the higher and to the right the R-P curve is, the better the model will perform.

$$F1 - score = 2 * \frac{P*R}{P+R} \quad (4)$$

B. Performance Analysis

In this study, YOLO algorithm is most popular and the most efficient algorithms are selected for face recognition purpose in the proposed system. In order to do fair comparison, we experimented various versions of YOLO algorithms in the same data to demonstrate which algorithm is better than others. The result of performance analyses shows that, among the models of YOLOv5, YOLOv5n with mAP = 0.77, F1-score=0.74, R=0.70 and P=0.78 is the smallest network model, which has only 1.9 million parameters. Because the models come in various sizes, the smaller model requires less time during diagnosing. As a result, the lowest time for the YOLOv5n model is required for the huge model, which requires more time.

V. CONCLUSION AND FUTURE STUDIES

Large data from sensors and energy meters demand extremely effective data processing systems, where contemporary technologies like Big Data and the Internet of Things have found their place in the development of energy applications. The advancement of new data mining techniques has outpaced the capabilities of conventional energy modeling and forecast techniques. Various smart technologies have been used to save energy. Traditional building energy modeling that uses software and statistical methods does not provide the need for quick and precise prediction required by decision-making systems. As a novel approach to energy modeling and assessment for many types of buildings, IOT models have demonstrated considerable potential. The pros and drawbacks of each model are discussed in this study, which gives an overview of IOT models used for benchmarking and predicting building energy usage.

In this paper, a YOlO method is used for facial recognition. And compared to all kinds of YOlO methods, the YOlOv5n method was the fastest and most efficient method. So, by using the YOlOv5s method on the Jetson Nano platform, it creates the possibility of authenticating the residents of the houses to identify them to turn on or off the sources of energy consumption in the houses. Therefore, the presented system is designed with the aim of optimizing energy consumption in houses and with the aim of ensuring the safety of the residents of the houses. Future research can focus on optimizing energy consumption strategies by developing advanced algorithms and techniques, such as reinforcement learning, to dynamically adjust energy usage based on authenticated residents' identities and preferences. Further study should address privacy and security concerns by exploring privacy-preserving techniques and implementing robust security measures to protect sensitive resident data during the authentication process in the facial recognition-based energy optimization system. Moreover, future studies on the use of Internet of Things in smart homes to optimize energy consumption will focus more on the use of mobile phone GPS. Moreover, The Intelligent Computational Engine will be created and used with the established electric energy consumption prediction models to achieve automated, real-time, and optimum control of electric energy consumption. This will reduce ineffective energy management, wasted energy resources, and high energy prices.

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